ARTIFICIAL NEURAL NETWORKS APPLIED TO REDUCE THE NOISE TYPE OF GROUND ROLL

P.L.B. SOARES[1], J.P. SILVA[1,2] and M.D. SANTOS[3]

[1] *Postgraduate Program in Communication Systems and Automation, PPGSCA - Federal University of Semiarid Region - UFERSA, Mossoro, Brazil.*
[2] *Department of Electrical Engineering, Federal University of Rio Grande do Norte - UFRN, Natal, Brazil.*
[3] *Department of Informatics, Federal University of Paraíba - UFPB, João Pessoa, Brazil.*
mdantas@ci.ufpb.br

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ABSTRACT

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Seismograms exhibit a good approximation of a geological structure. However, the images they show are generally contaminated by irrelevant information. The noise ground roll in these images can contribute significantly to the distortion of the data present in the desired information, due to the scattering of waves in deeper regions of geological layers. In this work, we used a method based on Haar and Daubechies wavelets applied in conjunction with artificial neural networks to reduce the noise ground roll. This type of noise is normally present in earth seismic images and it is similar to those found in oil reservoirs.

KEY WORDS: artificial neural networks, wavelets, ground roll, image processing.

INTRODUCTION

The geological region where oil is generated and stored is a complex and heterogeneous medium, generally kilometers deep in the crust and has a thickness of a few tens of meters (Linville and Meek, 1997; Yilmaz, 2001). The data of this medium can be obtained through direct methods, for example drilling, which has a high operating cost, or through indirect methods, for example seismic reflection or refraction, which are less expensive and presented a high accuracy (Corso et al., 2003). The reflection seismic is the main method

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used in the exploration of hydrocarbons, and provide important information about the subsurface and physical properties of the layers that compose it. By this method, we can observe the behavior of seismic waves that, after the penetration in the crust, are reflected due to discontinuities existing in the elastic properties of the medium and they return to the surface, where they are detected by geophones strategically arranged for this purpose.

The geophones capture the superposition of the reflections that represent individual physical amplitudes characterized by a temporal series (Thomas, 2001). Once this temporal series are registered, it constructs a seismogram which can be defined as a matrix where the columns represent the indices of receivers, and the lines are the indices of the time instants where to store the captured amplitudes waves. As the seismogram is represented by a matrix, it can be interpreted as an image where each matrix element corresponds to one pixel. From this identification, we can use the techniques or algorithms of image processing based on artificial neural networks (ANNs) applied in conjunction with wavelet transforms to eliminate the unwanted noise (Mallat, 1989; Deighan and Watts, 1997; Dash et al., 2012; Mishra et al., 2010; Santos et al., 2011; Saradhadevi and Sundaram, 2012).

The noise present in the images represents a great problem in seismic processing because it corresponds to an unwanted energy. This type of noise can mask relevant information about the geological structures of a particular area in exploration. Therefore, it is very important to reduce this noise. In seismic processing, we generally use a set of techniques that operate on the data to remove or minimize these undesirable events. This procedure is used to preserve the original characteristics of the images and provide the much information of the geological layers.

One of the main noises in land seismic is the rolling noise, usually called "ground roll". During the acquisition of seismic data, approximately two-thirds of the produced power corresponds to this type of noise, also known as Rayleigh waves (Leite et al., 2008). These types of waves propagate on the surface as rolling waves and are characterized by low frequency, low decay rate and high amplitude (Yilmaz, 2003). In this way, the amplitudes that constitute the ground roll do not contain information about the deeper geological structures, thereby becoming an unwanted signal. This type of noise is overlapping the interest layers, masking the important information about the interpretation of the images. The ground roll is always present in land surveys. In the seismograms it appears in cone geometric shape (Yilmaz, 2003).

In this paper, Artificial Neural Networks (ANNs) are used to recognize and attenuate the ground roll noise from land seismic images. The signals that represent the ground roll are extracted by using Haar and Daubechies wavelets. Images set with and without ground roll were used to train the neural network.

After the training, the network is able to identify and attenuate the ground roll noise in any seismic image that shows the same pattern identification. Fig. 1 represents the scheme used in this work to attenuate the ground roll noise.

This paper is organized as follows: in the Methodology section, a description is given about the sequence of steps to get the scheme shown in Fig. 1 using a mathematical procedure based on wavelets. In the ANN section, a brief description about neural networks and their training process is presented. Results and discussions are shown the next section, and finally, in the last, the main conclusions are presented.

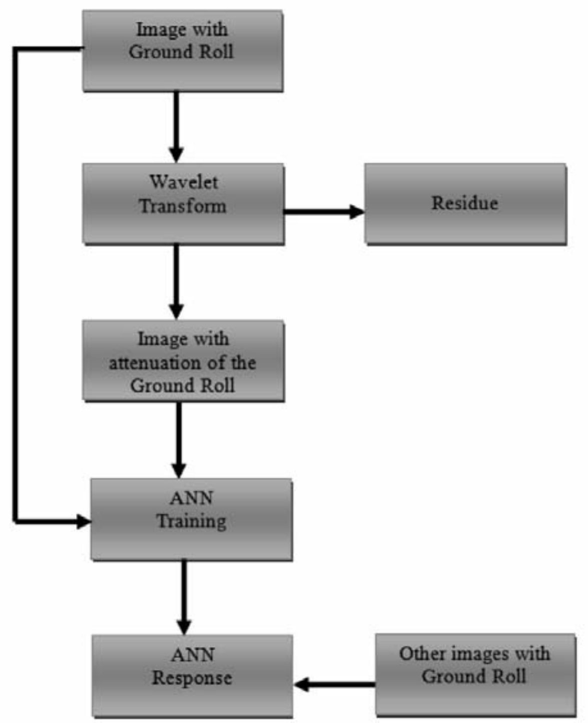

Fig. 1. Block diagram of the sequence of steps for attenuation of ground roll noise.

METHODOLOGY

To analyze the efficiency of the techniques used in this work we chose an image or data set known as Oz 25 (Yilmaz, 2003) shown in Fig. 2. This image contains a large amount of surface noise and whole data set of the center is contaminated by ground roll (region A). This type of noise can mask the view of interest events making interpretation of subsurface structures (region C). In region B there is the noise caused by the air waves that also contaminate the image.

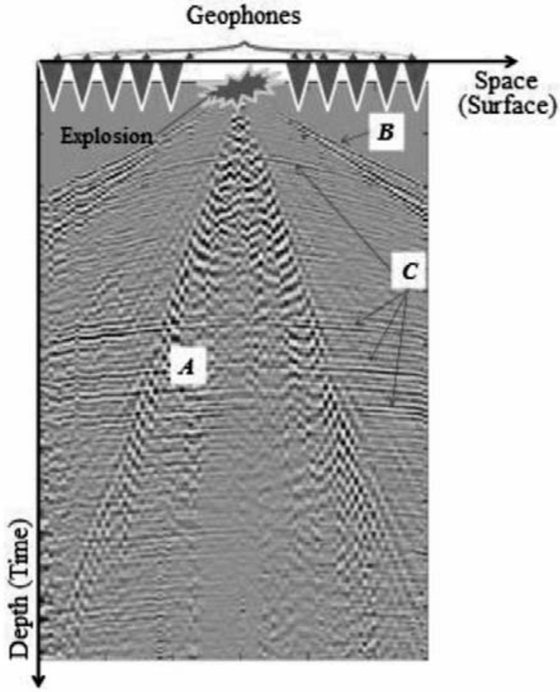

Fig. 2. Representation of the seismogram, where ***A*** is a region contaminated by surface rolling noise, ***B*** is the region contaminated by the shock wave, and ***C*** represents the reflectors of interest.

For the purpose of neural network training, the wavelets used in this work were of the type orthogonal of Haar (Pan, 2001) and Daubechies (Daubechies, 1988; Daubechies, 1990), applied in conjunction with the algorithms of analysis and decomposition proposed by Mallat (Mallat, 1989). The procedure is based on the decomposition and reconstruction of the images in various scales as shown in Figs. 3a and 3b. Through this technique we can obtain the characteristics present in the image considering each of the levels present in it.

In addition, to minimize the noise rolling surface, we use the decomposition process in multi-scale shown in Fig. 4.

In the multi-scale decomposition process, the noise present in the image is restricted to the coefficients of the larger scales, in other words this noise can be considered as low frequency noise that can be visually located. Thus, the filtering procedure consists in attenuate the wavelet coefficients in the correspondent region to the noise energy. Using these techniques in the image processing, it's possible to make an analysis in different resolution levels to estimate the contribution of each type of wavelet to reduce the ground roll noise.

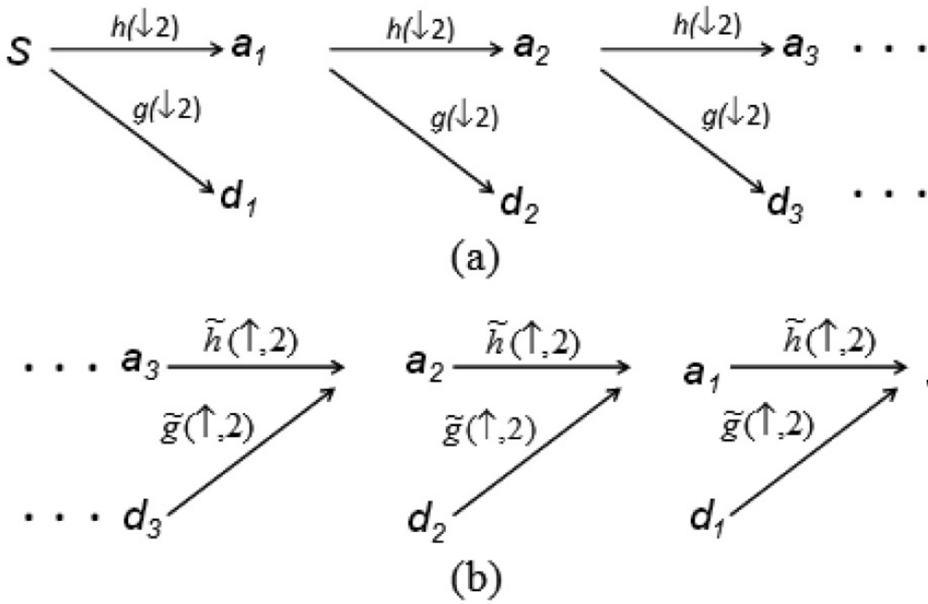

Fig. 3. Algorithm representation: (a) of analysis and rapid decomposition with filters h and g followed by a decimation of ($\downarrow$2); (b) of analysis and fast reconstruction with filters $\tilde{h}$ and $\tilde{g}$ followed by an insertion ($\uparrow$2).

ARTIFICIAL NEURAL NETWORKS

Description of neural networks

Artificial neural networks are computer systems based on the belief that intelligence is achieved by a large number of interactions of simple processing units called nodes or neurons (Shi et al., 2006). These interactions are achieved by algorithms, such as the backpropagation, one of the most used in neural networkstraining.

Kaliraj and Baskar (2010) report that there is not analytical method to choose the number of layers and neurons of a neural network, since these should be determined experimentally by trial and error and Ma et al. (2009) concluded that a neural network has typically three or more layers (input, middle or hidden, and output) as shown in Fig. 5.

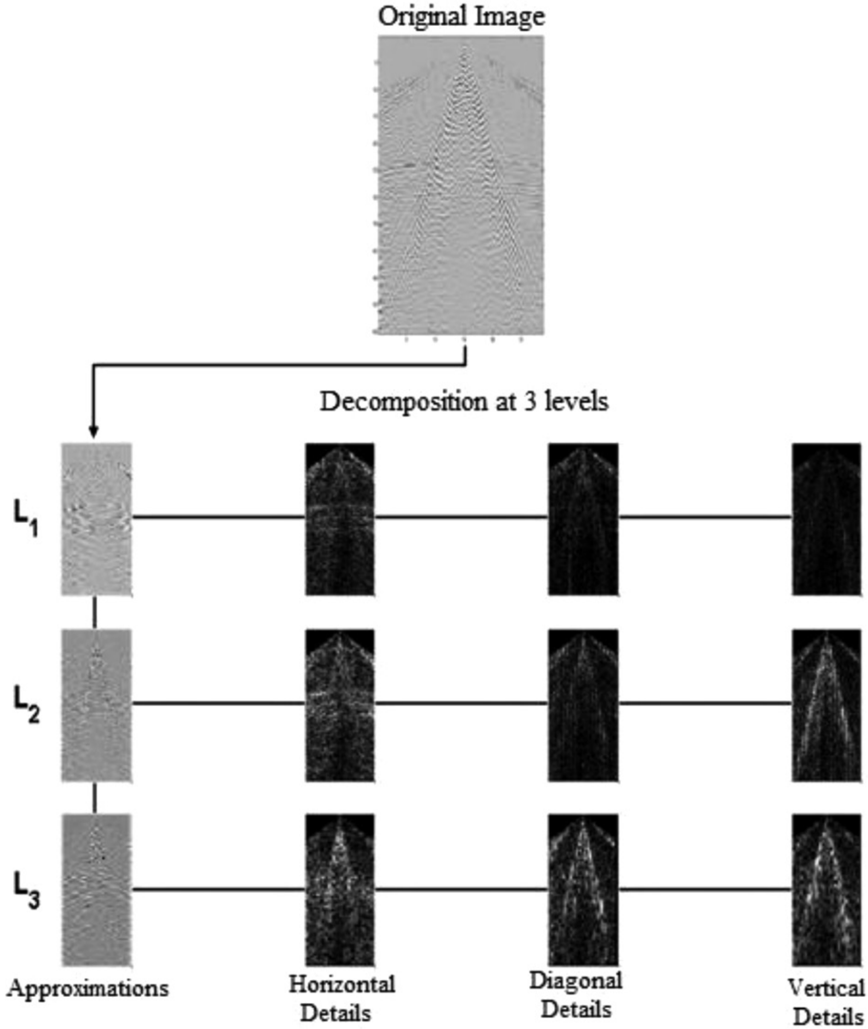

Fig. 4. Representation in 3 levels of resolution through the wavelet decomposition method for the seismogram shown in Fig. 2.

The architecture of the neural network shown in Fig. 5 is the feed-forward type, i.e., each layer is connected to the next. The number of neurons in the input layer depends directly on the number of features extracted from the object studied to determine a certain pattern. The number of neurons in the output layer is directly related to the number of desired information for the analysis. The number of neurons in the hidden layer depends on the complexity of the problem to map the set of inputs and outputs. Fig. 6 shows an example of how to calculate the number of neurons in each layer for a given object under examination, in this case, the human face.

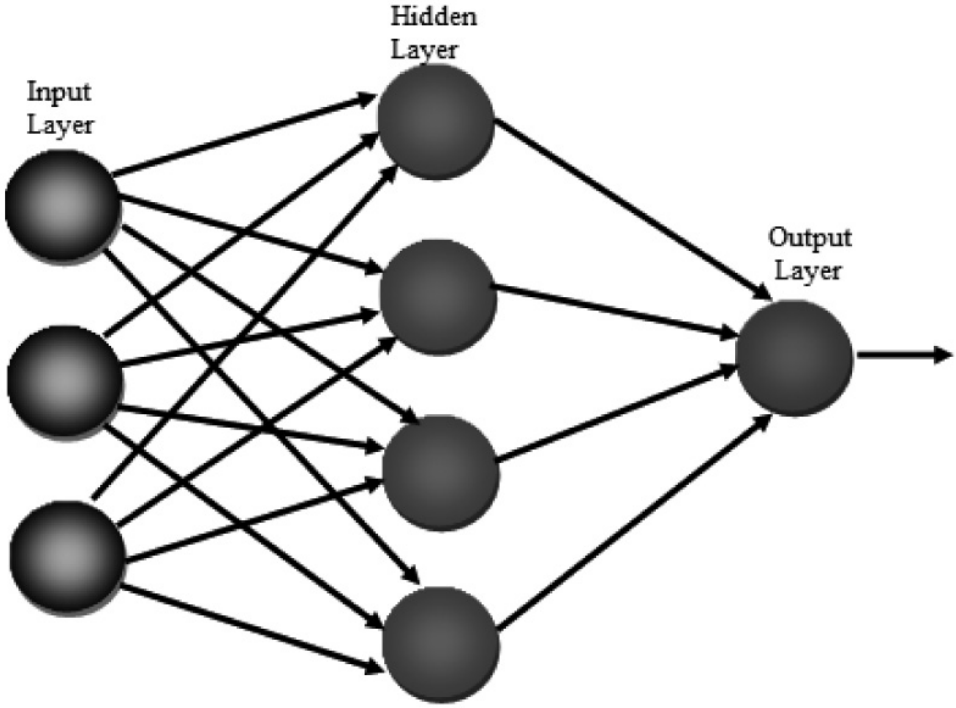

Fig. 5. Representation of the various layers of the neural networks.

In this example, the goal is to map features of the human face, such as eye color, hair color and skin color, and through them get information about the person who owns the referred face. Information that may be released by the network, in this case, is the height and the continent in which the person was born. In this analysis, the quantity of input neurons is the same quantity of characteristics (eye color, hair and skin) and the output neurons correspond to the number of information desired. This mapping may or may not be obtained depending on the layers and hidden neurons quantity.

The learning of a neural network is obtained through its training. In this work, the network training process is based on a supervised model. For the case of a feed-forward type network, its training occurs when the input/output set is known. In addition, to train a feed-forward network, the weights should be adjusted until the results become similar to the output of the training set, or that certain limit of repetitions (epochs) is reached. When the training process ends, the neural network is ready to simulate inputs that were not seen in training.

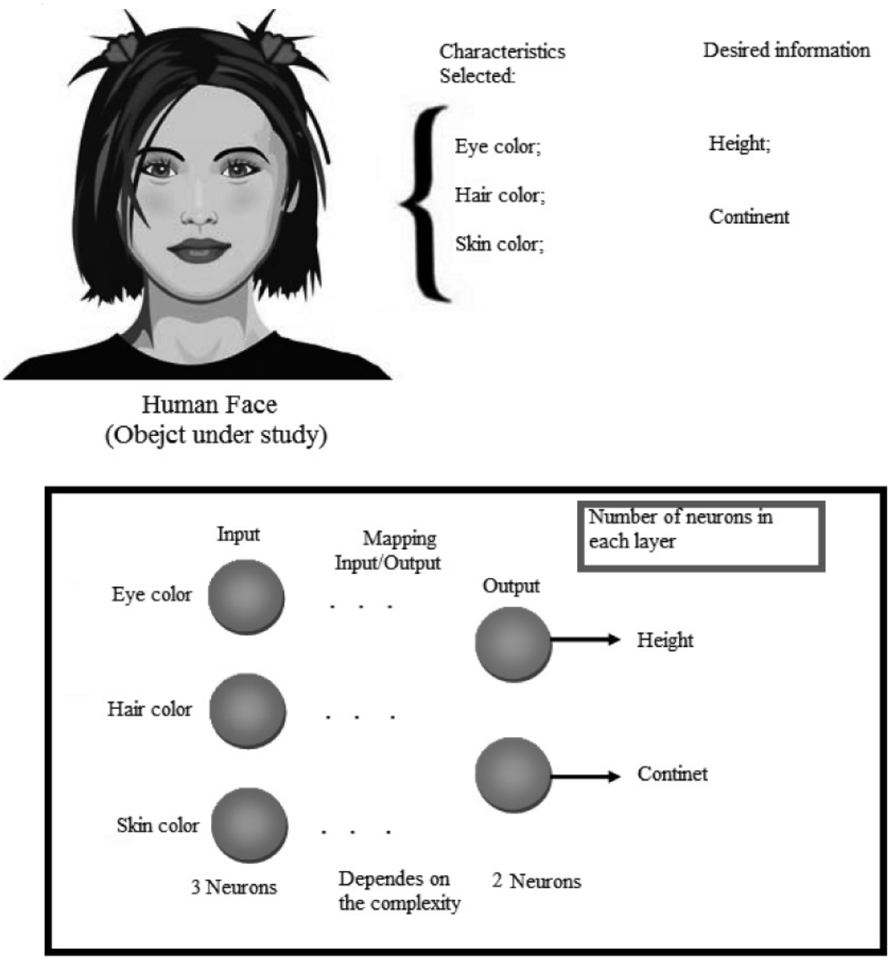

Fig. 6. Example of how to calculate the number of neurons in each layer.

Training neural networks

The training set formation is supported by the window of order 3, illustrated in Fig. 7, where x1, x2, ... , x8 is the 8-neighborhood of xC (Filho and Neto, 1999). The window makes one complete scan in the images with and without ground roll, Figs. 11(a) and 11(b), respectively. The input data for training are taken from the image with ground roll and the output data are taken from the image with attenuation of ground roll.

Fig. 8 shows how the procedure to capture the input and output data is done. At the time that the window scans over the images, the 8-neighborhood image with ground roll is stored to form the input set of the network, as well as the desired output (center pixel) of the image with ground roll attenuation performed by wavelet, is stored to form the output set. Thus, after training, the network acquires the ability to map any image with ground roll noise and provide an image with that noise attenuated.

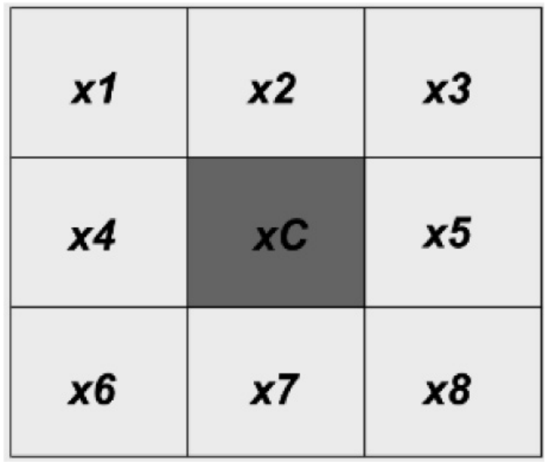

Fig. 7. 8-neighborhood of xC.

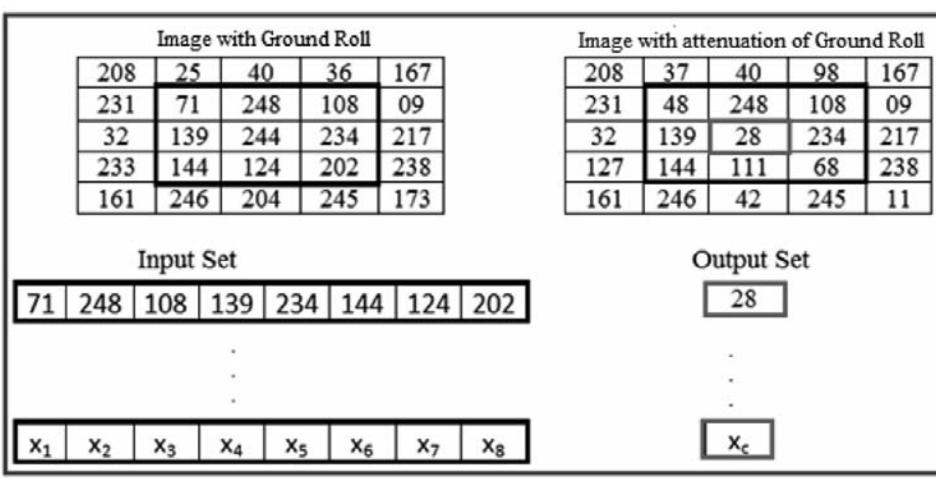

Fig. 8. Set of input/output data.

The configuration of the neural networks used in this work has three layers, the input layer has 8 neurons which correspond to the 8-neighborhood of the center pixel. The output layer has only one neuron corresponding to the value mapped by the network. The hidden layer, which was obtained through some experiments, used 16 neurons. Thus, the architecture of the neural network that achieved the best performance in terms of desired error has the following structure: 8-16-1. The proposed structure is shown in Fig. 9. The hidden and output layers were configured with sigmoid (logsig) and linear (purelin) activation function, respectively. The NN-2 was trained by using the back-propagation algorithm with a maximum number of 100 times, learning rate of 0.47 and desired error of 10^{-3}.

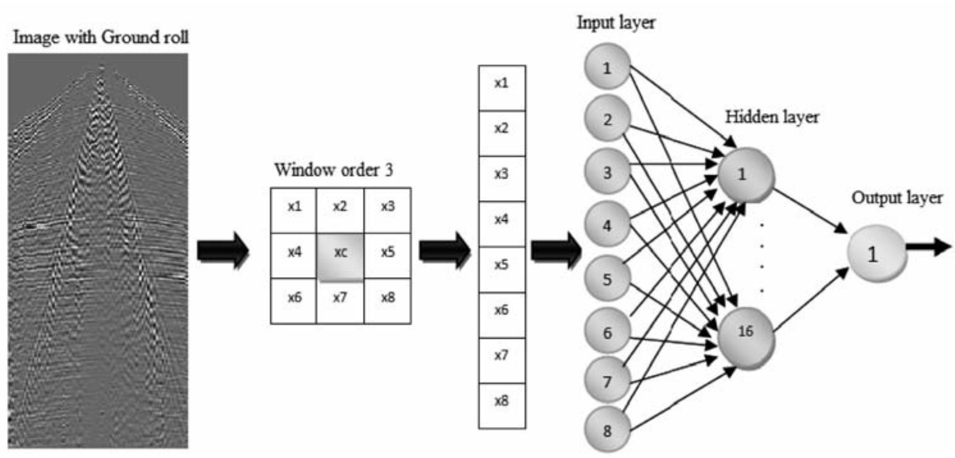

Fig. 9. Neural network structure.

RESULTS AND DISCUSSION

To enable the filtering process, we define a cut-off threshold of the wavelet coefficients to maximize the removal of noise from visual inspection of the image. The choice of threshold depends on the amount of visual noise present in seismic data. Thus, in all simulations with neural networks, the image treated with wavelet decomposition multi-scale was taken as the basis for training.

Fig. 10 shows a comparison between the original image similar to a seismogram containing the ground roll, shown in Fig. 2, and the image after filtering the ground roll using the Haar wavelet on the eighth level of resolution. It is observed that the characteristics of the original image are preserved in the regions of interest and a portion of the noise was almost imperceptible removed.

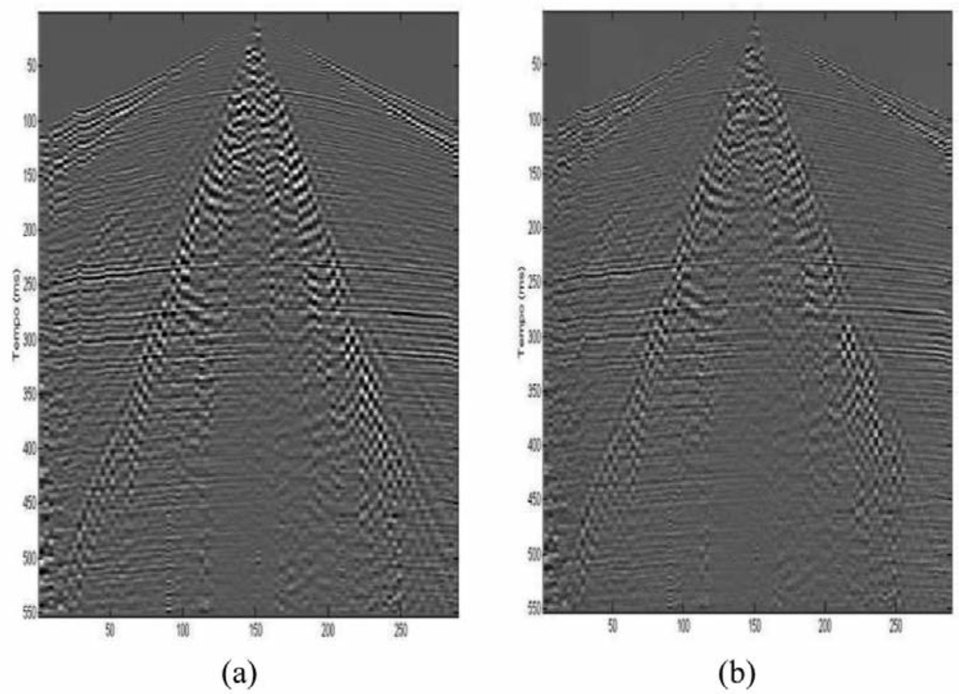

Fig. 10. Comparison of signals: (a) Original image containing the ground roll and (b) Image with attenuation of ground roll through multi-scale decomposition using Haar wavelet.

Next, the Daubechies wavelet was used in the original image shown in Fig. 2 for filtering noise. Fig. 11 shows a comparison between the original image and the image after filtering the ground roll using Daubechies wavelet on the eighth level of resolution. It can be seen that, through this wavelet transform, there was significant removal of noise, preserving mainly the original characteristics of the image in horizontal lines which provided the information of greatest interest to the analysis of seismic records in oil reservoirs. Fig. 12 shows the residue removed through Daubechies wavelet.

In observation, it is emphasized that, for greater efficiency of the technique used, this process can be repeated considering only sub blocks of the image matrix associated, i.e., it is considered parts of this image where there is a greater presence of noise.

After using the Haar and Daubechies wavelet, we perceive visually that the Daubechies wavelet obtained better performance in ground roll noise attenuation. Thus, the images in Figs. 11(a) and 11(b) were used to compose the input and output set, respectively, for the training of the neural network specified in subsection B. After the training step, in order to verify the performance of the network as a filter for ground roll noise, the image shown in Fig. 11(a) was again used as input of the network, as result after simulation process, we obtain the image shown in Fig. 13.

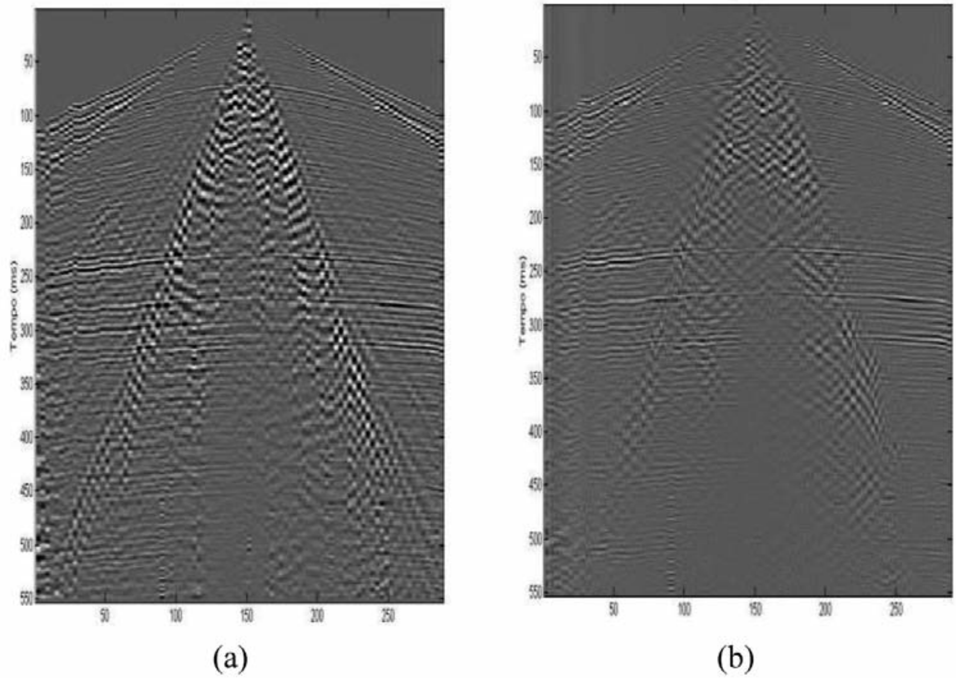

Fig. 11. Comparison of signals: (a) Original image containing the ground roll and (b) Image with attenuation of ground roll through multi-scale decomposition using Daubechies wavelet.

CONCLUSION

In this paper, the multi-scale decomposition approach, using the Haar and Daubechies wavelets were successfully applied in conjunction with artificial neural networks in the analysis of seismic records similar to those found in oil reservoirs. The results show that it is possible through Daubechies wavelet to train a neural network to obtain a better view in image after removal of ground roll noise. From the study presented in this paper, one can see clearly that the choice of appropriate wavelet is of fundamental importance to the training of the neural network and optimization of the filtering process for withdrawal or removal of ground roll noise. Despite the complexity, the method presented is another tool available to geologists to assist in noise attenuation and identification of fractures in order to integrate the information of new oil wells.

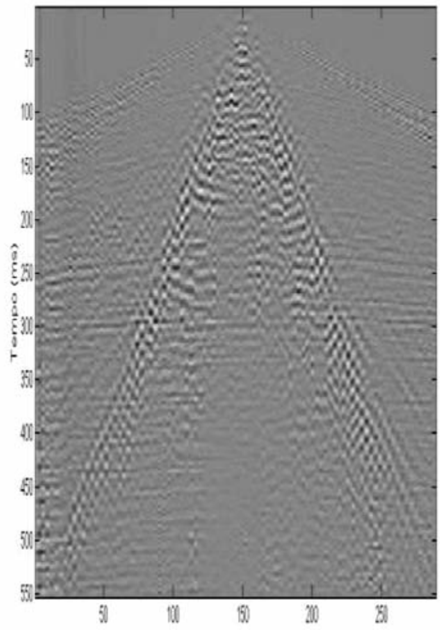

Fig. 12. Residue removed through Daubechies wavelet.

Fig. 13: Ground Roll Attenuation using neural network.

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